Is Innovation a Factor in Merger Decisions? Evidence from a Panel of U.S. Firms

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Abstract

The impact of innovation on mergers has been a source of debate in merger enforcements. Innovative firms influence market structure by changing merger decisions, as mergers provide resources for commercialization of innovation and capturing knowledge spillovers. However, there is a limited empirical evidence on the innovation induced changes of merger likelihood. We construct panel data of mergers among publicly traded U.S. manufacturing firms from 1980 to 2003 and investigate the impact of innovation, measured by a citation weighted patent stock, on merger decisions controlling for business cycles and proxies of neoclassical, behavioural, and Q theories of mergers. We find that innovations are positively and significantly correlated with firms' merger likelihood, and these decisions are procyclical. The positive impact of weighted patent stocks on merger decision is robust to the mixed model estimation method, and innovation effects on merger decisions vary across industries.

Keywords: Merger, Innovation, Business Cycle, Anti-trust, Competition, Patent

JEL Classification Numbers: L12, L22, L40, L44, L60, O31, O34

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1 Introduction

A great deal of merger activity takes place in high-tech and innovative industries (De Man and Dysters, 2005; Chirgui, 2009), which may imply a relation between innovation and mergers. Kats and Shelanski (2005, 2007) refer to this effect as “innovation impact criterion.”Mergers might be appealing for innovative firms, as they are often a more efficient approach to increasing capacity than direct investments (Becketti, 1986). Thus, innovative firms can raise their required capacity and resources for commercialization of their innovation through mergers. Mergers can also help the innovative firms to capture their knowledge spillovers, decrease competition in innovation, and improve their innovation potential. Capturing spillovers via mergers occurs also in the airline industry where firms merge to internalize their network externalities. Innovative firms may also merge to combine their R&D resources, learn from each other, and dampen competition in their market (Huck et al., 2000). As an example, Jost and Velden (2008) discuss the development of a new drug in the pharmaceutical industry, which takes several years and large investments. The requirement for large investments has led to mergers between large companies in this industry, such as GlaxoWellcome and SmithKlinee Beecham in 2001 and Hoechsr and Rhone Poulenc in 1998 among many others.[1]

Despite the convincing arguments offered in the literature on the impact of firms' innovation on their merger decision, there is a limited empirical evidence on this effect. Frey and Hussinger (2006) find that stock of patents as a measure of innovation has a negative impact on the probability of being a target firm in mergers. Ali-Yrkko (2006) does not find any significant effect of the high quality patents of target companies on their probability to be acquired. Blonigen and Taylor (2000) also find that acquiring firms are after target companies with high quality innovations. Bena and Li (2014) focus on the empirical relation between innovation and mergers, but their study examines the influence of the resulted synergies from combining innovations in the merger process. They find that synergies resulted

[1] Kaplan (2000, p.5) also shows that technological innovations matter in merger decisions in a summary of few studies. For example, Kaplan (2000, P.40) shows that hospital mergers are a result of technological change that decreases the demand for inpatient care.

from combining innovation drive acquisitions. In this paper, we use the U.S. firm level data to provide empirical evidence for how acquiring firms' innovation influences their merger likelihood. We measure innovation with citation-weighted patent stocks following Aghion et al. (2005), Hall et al. (2005), Stahl (2010), and Entezarkheir and Moshiri (2016).[2]

The result of our study will offer useful insights for policy makers. It is well-established that innovation is imperative for economic growth (Grossman and Helpman, 1991; Aghion and Howitt, 1992) and improves consumer welfare by lowering costs and providing new products. Innovation incentive mechanisms, such as intellectual property rights, tend to encourage innovation by granting monopoly rights to innovators. On the other hand, the traditional merger enforcement is after increasing consumer welfare through promoting market competition and lower prices.[3] Even though ultimately both the innovation incentive mechanisms and the anti-trust regulations aim to improving consumer welfare, they have a different focus and implications for economic growth and prices. This fact raises the question of how the traditional merger process with the objective of promoting more competition and lower prices can take into account the possible impact of innovation on the evolution of market structure and competition in merger investigations. Studies focusing solely on price changes and competition in the merger analysis might miss an important likely influence of innovation on merger decisions.

We also examine the procyclicality of mergers at the firm level and provide evidence on the effect of both innovation and business cycles in merger activities. The literature supports the procyclicality of mergers (e.g., Jensen, 1993; Shleifer and Vishny, 1992). If there is a prediction of higher demand, firms can increase their production capacity through mergers. However, the empirical evidence is mixed. For instance, Maksimovic and Phillips (2001) and Komlenovic et al. (2011) provide evidence for the procyclicality of mergers at the aggregate and industry level. However, Weston (1961), Nelson (1966), Melichner et al. (1983), and

[2]Other measures of innovation are discussed in section 2.

[3]The pro-competitive attitude of merger enforcement is based on section 7 of the Calyton Act which makes the acquisition of the stock or assets of other firms illegal if the acquisition substantially lowers the competition or creates a monopoly.

Beckettie (1986), focusing on aggregate mergers, do not support the procyclicality of mergers. To the best of our knowledge, no previous study has examined the procyclicality of mergers at the firm level. The advantage of the firm-level study on the procyclicality of mergers is that decisions are actually made at the firm level not the industry level and the pre-merger information of targets and acquirers does not disappear in the aggregation process of mergers. Therefore, the firm level study will shed more light on the merger decision process.

The question on driving factors of merger waves is still open in the literature (Brealey et al., 2012). Previous studies offer neoclassical, behavioural, and Q-theories of mergers to explain merger waves. The neoclassical theory focuses on industry shocks, such as anti-trust policies and deregulations, as main forces behind the merger waves (Gort,1969; Harford, 2005; Mitchell and Mulherin, 1996; Andrade and Stafford, 2004; Komlenovic et al., 2011). The behavioural theory's reasoning for mergers is a temporary stock mis-evaluation of firms (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004). The Q-theory of mergers argues that firm's with high Tobin's Q can profitably expand through mergers (Hasbrouck, 1985; Jovanovic and Rousseau, 2002). Nevertheless, as stated in Brealey et al. (2012), these theories have not been able to fully explain merger waves. Our study adds to this line of research by analyzing the impact of innovation in merger decisions of firms.

The impact of innovation on mergers might be influenced by the reverse causality between mergers and innovation. Economic literature offers a long list of studies on the impact of market structure on innovation. Some studies suggest that more competition is better for innovation, as firms in a competitive market are under constant pressure to lower costs, improve the quality of their products, or increase the scope of their production (e.g., Arrow, 1962; Reinganum, 1983, 1984, 1985; Czarnitzki and Kraft, 2004; Loecker, 2011). Other studies offer an opposite view that higher market concentration is better for innovation due to economies of scale and an ability to handle risks associated with large R&D investments (e.g., Schumpeter, 1942; Gilbert and Newbery, 1982; Stoneman and Battisti, 2010, p.748). More recent empirical studies make a connection between the two varying views on the impact of competition on innovation. For instance, Aghion et al. (2005) find an inverted U-shaped relation between innovation and competition. At low levels of competition, innovation increases with competition, but at high levels, innovation decreases with competition. However, Correa and Ornaghi (2014) cast doubt on the inverted U-shaped relation and provides a causal positive impact from competition to innovation. A number of studies in the literature also investigate the role of mergers in innovation (e.g., Stahl, 2010; Szucs, 2014; Entezarkheir and Moshiri, 2016). Given some evidence on the potential simultaneity bias in the impact of innovation on mergers, we use an instrumental variable approach in our estimation method to address the problem.

We build a panel of more than 6,000 publicly traded merging and non-merging U.S. firms in the manufacturing sector from 1980 to 2003 with 800 merging pairs of firms. A unique aspect of this data set is that it has information not only on merged entities in the merging year and post-merger period similar to previous studies, but also on both target and acquiring firms in the pre-merger period.

Our findings based on a panel logit estimator suggest a positive correlation between innovative activities of firms and their merger decisions, which supports the argument by Kats and Shelanski (2007) that merger activities are mostly taking place in innovative industries. We also find evidence for the procyclicality of mergers at the firm level. The instrumented impacts of innovation on the probability of mergers also show positive and comparable effects from innovation. This result implies that the internalization of knowledge spillovers and the need for resources to commercialize innovation may create incentives for firms to merge. Our results do not provide support for the role of the relative valuation of firms in merger decisions based on behavioural and Q-theories of mergers. We, however, find supporting evidence for the excess capacity hypothesis of Danzon et al (2007), which is an increase in Tobin's q lowers merger likelihood. They argue that firms with higher expected growth will have a large Tobin's q and less incentive to merge, but firms without a promising future will have lower Tobin's q as a result of their lower future cash flows and are more likely to merge. We also find that the impact of innovation on merger decisions is conditional on acquiring companies' industries, which implies a need for treating merger applications of various industries differently.

This study offers some insights for anti-trust policies, as its findings provide evidence for the positive role of innovation in promoting mergers that result in larger and less competitive firms in the manufacturing sector. It is true that more competition can decrease prices which is beneficial for consumer welfare. However, limiting mergers, and consequently increasing competition can have an adverse effect on innovative firms, since it may reduce their ability to capture their knowledge spillovers and reap all the benefits of their innovations. Such firms might decrease their innovation activities, which will lead to fewer new products and lack of quality improvement that can adversely affect consumer welfare. Therefore, the losses of less competition and higher prices on consumer welfare by mergers should be weighed against the benefits from more innovation when deciding on merger applications.

2 Empirical Framework

Our empirical analysis is based on the following panel logit regression equation, in which the merger likelihood of firms $Prob(Merger_{it})$ is explained by citation-weighted patent stock ($logCitationPatent_{it-1}$) as a measure of innovation and a series of controlling variables,

$$Prob(Merger_{it}) \;\; = \;\; \beta_0 + \beta_1 logCitationPatent_{it-1} + X_d + \alpha_i + \epsilon_{it}, \qquad (1)$$

where i stands for firm, and t for year. The variable X_d is a set of control variables, which are explained in section 2.1.

The variable $Merger_{it}$ is an indicator variable which is equal to 1 when a firm experiences a merger and zero otherwise. Gugler and Siebert (2007) use this measure of merger in their investigation of the impact of mergers on market share. The commonly used proxies of innovation in the literature are Solow residuals or total factor productivity (TFP), R&D expenditures, and patent counts (Blundell et al., 1999). TFP is measured from data on inputs and outputs, which make it prone to measurement errors and biases, when information on inputs and outputs is not readily available (Keller, 2010 p.804). Using R&D as a measure of innovation has limitations as well. First, R&D activities do not necessarily lead to desired outcomes; second, R&D is not reported by many firms; and third, R&D is an input rather than an output (Keller, 2010 p.804). In contrast, patent counts record the output of innovative activities. However, some innovations are not patented, and many patents represent a very small innovation (Hall and Trajtenberg, 2004). Some of the more recent studies, such as Hall et al. (2005), have partially addressed these issues by employing a citation-weighted patent stock measure for innovation that treats the value of each patent equal to the number of its citations.

Using the rich data on patents and citations available in our sample of analysis, we also construct the citation-weighted patent stock measure as a proxy for innovation.[4] This measure is based on a declining balance formula, $CitationPatent_{it} = (1-\delta)CitationPatent_{it-1} + flowCi_{it}$, with the depreciation rate of δ=15% (Hall et al.,2005 and Noel and Schankerman, 2013).[5] The variables $CitationPatent_{it}$ and $flowCi_{it}$ stand for citation stock and citation counts of firm i at time t, respectively. The variable $flowCi_{it}$ is the number of citations that each patent document receives.[6] Therefore, we take into account not only the output of the innovative activity but also the quality of the innovation via its citations in our measure for innovation. The variable $logCitationPatent_{it-1}$, is the one period lagged logarithm of the citation-weighted patent stock of firm i in year t. We use the lagged innovation as innovation will take some time to influence firms' merger decisions. As a robustness check, we also estimate equation (1) with R&D intensity as an alternative measure of innovation in section

[4]There is a caveat in using this measure of innovation, as some firms might patent defensively (Hall and Ziedonis, 2001; Ziedonis, 2004; Noel and Schankerman, 2013), which might lead to patents on marginal innovations. We will use other measures of innovation as a robustness check.

[5]Most researchers settled on δ=15% (e.g., Hall et al., 2005). Hall and Mairesse (1995) apply alternative deprecation rates and conclude that changing the rate from 15 percent does not make a difference.

[6]We define the initial stock of citations as the initial sample values of citation counts similar to Noel and Schankerman (2013).

4.

As a result of a gap between the application and grant date of patents, the data on patents and their citations are truncated. Patents with an application date close to the end of the sample might be granted out of the reach of the sample. Similarly patents in the sample might receive further citations outside the sample period. We correct for these truncations in building the variable $logCitationPatent_{it}$ in equation (1). See appendix A for detailed correction procedures. The variable α_i represents possible unobserved heterogeneities among firms that might arise from different firm characteristics and performances.[7]

2.1 Control Variables

The literature suggests several variables that matter in merger decisions. These variables include factors suggested by the neoclassical, behavioural, and Q theories of mergers, business cycles, and a group of other factors. In our investigation of the role of innovation in merger decision of firms, we also control for these variables.

The variable BC_{t-1} in equation (1) controls for the impact of business cycles on firms' merger likelihood. The mergers are claimed to be procyclical, as a boost in current economic activities predicts an increase in the future demand, which requires an increase in the capacity of production (Becketti, 1986; Jensen, 1993; and Shleifer and Vishny, 1992). The response to increasing demand can be either internal investments or mergers. The choice of merger is more appealing, as the acquiring company can increase the production capacity much faster. However, the empirical literature does not offer much evidence for procyclicality of mergers. A group of early studies, such as Weston (1961), Nelson (1966), Gort (1969), Melichner et al. (1983), and Beckettie (1986) examine the impact of economic activities on aggregate mergers, but they do not reach a consensus in their findings. Maksimovic and Phillips (2001) provide evidence for procyclicality of aggregate mergers, and Komlenovic et al. (2011) show the procyclicality of mergers at the industry level.

[7] We do not control for target firms' fixed effects separately as we assume targets are selected at random by acquiring firms and they do not play a role in the decision making process of mergers.

Our study also examines the procyclicality of mergers but at the firm level. To our knowledge, none of the previous studies investigate the procyclicality of mergers at the firm level. The advantage of a merger study at the firm level is that the pre-merger information of targets and acquirers does not disappear in the aggregation process of mergers into industry level. We consider a lag of business cycles as they require some time to show their effect on merger decisions.

Similar to Komlenovic et al. (2011), we use the Chicago Fed National Activity Index (CFNAI) as a measure of business cycles. This index is a weighted average of 85 indicators for current economic activities and its variations show deviations from the trend.[8] When CFNAI is positive, it corresponds to growth above trend, and when CFNAI is negative, it translates into growth below trend. The value of zero for the index implies growth at trend. The other measures of business cycles previously used in the literature are National Bureau of Economic Research (NBER) business cycles dates. For example, McQueen and Roley (1993) used the single series on industrial production as a measure of business cycles. The reported status of the economy by the NBER dates, however, has considerable lags, which devalues the provided information for company managements in their decision makings. For example, NBER announced the through in the business cycle of June 2009 on September 20, 2010.[9] The CFNAI index is built upon economic data present at the estimation time.

The neoclassical theory explains merger waves by industry shocks, such as changes in anti-trust policies and deregulations (Gort,1969). Harford (2005), Mitchell and Mulherin (1996), and Andrade and Stafford (2004) provide evidence for a positive relation between number of mergers in an industry and industry shocks that take place right before mergers. Komlenovic et al. (2011) and Harford (2005) also report a positive correlation between industry shocks and mergers at the industry level. Mitchell and Mulherin (1996), Mulherin and Boone (2000), and Andrade et al. (2001) show that merger activities are generally

[8]For a detailed explanation of series used in building CFNAI index see Komlenovic et al. (2011) and www.chicagofed.org/publications/cfnai/index

[9]This information is available at: http://www.nber.org/cycles.html

concentrated in a few industries at a time. Thus, we think that mergers at the firm level are also under the influence of these shocks in their merger decisions.

We include different measures of industry shocks to control for the neoclassical factors in the firms' merger decisions (Harford, 2005; Komlenovic et al., 2011). These measures include asset turnover ($Asset\, Turnover_{it}$), employee growth ($EmployGrowth_{it}$), sales growth ($SaleGrowth_{it}$), profitability ($Profitability_{it}$), measured by net income divided by sales, ROA (ROA_{it}), and capital expenditures ($CapitalExp_{it}$).[10] Mitchell and Mulherin (1996) show that changes in regulations also have positive effect on mergers, but since our period of study does not include those changes recorded by Harford (2005), they are not applicable to our estimations.[11]

The behavioural theory explains the merger decisions by a temporary stock mis-evaluation by merging firms. In other words, overvalued firms acquire the undervalued firms, and this mis-evaluation drives merger waves (Shleifer and Vishny, 2003; Jovanovic and Rousseau, 2002). To test the theory, one can investigate whether the ratio of market value to book value is higher when merger activities are increased. Ang and Cheng (2006), Dong et al. (2006), and Rhodes-Kropf et al. (2005) find that in merger transactions with stocks, the acquirer is more over-valued and the target is more under-valued than when the merger transaction is done by cash. Additionally, Rau and Vermaelen (1998) provide evidence for the under-performance of overvalued acquirers regardless of using cash or stock in merger transactions. Loughran and Vijh (1997) show that acquiring companies that use stock in their merger transactions have negative long-run abnormal returns, while in cash merger

[10]Harford (2005) and Komlenovic et al. (2011) use the first principal component of $AssetTurnover_{it}$, $EmployGrowth_{it}$, $SaleGrowthit$, $Profitability_{it}$, ROA_{it}, and $CapitalExp_{it}$ to measure industry shocks. Their rational for using the first principal component of these variables is the high level of multicollinearity among them. However, we do not find the problem at the firm level data, and, therefore, we use the six variables above directly in equation (1). As a robustness check and to compare the results, we will also report our estimates of equation (1) with the fist principal component of these variables in section 4.

Harford (2005) and Komlenovic et al. (2011) further include R&D among the variables in their principal component measure but this variable is highly correlated with our key variable of interest, the citation weighted patent stock. Thus, we do not include it separately.

[11]As a robustness check, we estimated equation (1) controlling for these regulation changes but our estimated coefficient of $logCitationPatent_{it}$ did not change.

transactions, the long-run abnormal returns of acquirers is positive. Rhodes-Kropf and Viswanathan (2004) also find that in overvalued markets, acquirers overestimate the value of target companies, and in undervalued markets, they underestimate the target's value.

The Q-theory of mergers suggests that as Tobin's q of a firm, measured by the ratio of market value to replacement cost of capital of a firm, increases, it becomes more fruitful for this firm to acquire other companies. Jovanovic and Rousseau (2002) find that the impact of a change in a firm's Tobin's q is larger for merger investments than direct investments. Hasbrouck (1985) and Jovanovic and Rousseau (2002) also show that firms with large Tobin's q are more likely to acquire companies with low Tobin's q. The evidence from the literature leads us to predict that the ratio of market value ($MarketValue_{it}$) to book value (TA_{it}) or Tobin's q ($Tobin'sq_{it}$) should be positively correlated with mergers. Thus, we also control for Tobin's q in equation (1). Following Hall et al. (2005), the market value of a firm is calculated as the sum of the current market value of common and preferred stocks, long-term debt adjusted for inflation, and short-term debts of the firm net of assets. Also the variable TA_{it} is measured by the book value of firms based on their balance sheet. The book value of a firm is calculated as the sum of net plant and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles and others. All of the components of TA_{it} are adjusted for inflation.[12]

We also use other control variables suggested in the literature as determinants of mergers in equation (1). For instance, we control for the concentration in the industry of firms (HHI_{jt}) and the annual capacity utilization ($CapacityUtil_t$) used by Andrade and Stafford (2004). The variable HHI_{jt} is the concentration in the industry (j) of firm i in year t, which is calculated by the summation of squared market shares of firms in that industry. The market share of firm i in year t is measured by the ratio of the firm i's sales in year t to total sales of primary four-digit standard industry classification (SIC4) that firm i belongs to in year t. This method of calculating market share follows Blundle et al. (1999), who

[12]Inflation adjustments are based on the CPI urban U.S. index for 1992 (Source: http://www.bls.gov).

employ sales in the primary SIC3, Giroud and Mueller (2010), who use sales in the primary SIC2 and SIC4, and Duso et al. (2014), who utilize sales in the primary SIC4. We would have liked to build the market share variable at a more disaggregate level, but our data only provide information at the SIC4 level. As Duso et al. (2014) notes, using SIC4 level information to define market share might generate lower bound estimates, as the relevant anti-trust market might be smaller than the product markets defined by SIC4. In the case of a merger, $MarketShare_{it}$ in the pre-merger period and in the merging year is measured by the combined market share of acquirer and target, and in the post-merger period is measured by the market share of the merged entity. In the pre-merger period and the merging year, if the four-digit SIC codes of the target and acquirer are the same, we assume they are in the same market and find the average of their market share, as we assume market demand should be divided equally between them. In the case of different SIC codes, we assume they are not in the same market, and we add their market shares to find the combined share, as each of them is faced with its own market demand. For non-merging firms, $MarketShare_{it}$ is the market share of non-merging firm i in year t. The variable $CapacityUtil_t$ only varies over years in our sample of analysis.

Akin to Harford (2005) and Komlenovic et al. (2011), we also includes excess cash ($logExcCash_{it}$), which is cash level in current year for firm i minus the arithmetic mean of cash over the sample period in equation (1). To control for financial constraints, we include the ratio of debt to equity ($Debt/Equity_{it}$), which is the ratio of total debt to shareholder equity multiplied by 100, and the logarithm of cash and cash equivalent ($logCash_{it}$) in our estimation model. Table 1 in the appendix describes the control variables in detail. We estimate equation (1) with a logit estimator for panel data.

There is a possibility of simultaneity bias in the impact of innovation on merger decisions. Since mergers result in larger and less competitive firms, they might improve innovation incentives due to economies of scale and scope, improved ability in handling risks of large R&D investments, and a broader knowledge base (e.g., Schumpeter, 1942). Mergers might also discourage innovation by eliminating competition, increasing costs, and decreasing production efficiencies (e.g., Arrow, 1962). For a list of studies on market structure and innovation see Entezarkheir and Moshiri (2016). Our strategy to tackle the possible endogeneity is to use previous citation-weighted patent stocks of firms to isolate the exogenous impact of innovation on merger decisions. This instrument is a relevant instrument, as the citations received to patent documents of firms in previous years, which are used in building our innovation measure, should not have any significant impact on their current merger decision, while we note that the value of each patent is equal to the number of citations of that patent in our measure. The instruments that we use are the second and third lags of the citation-weighted patent stock.

3 Data

We construct a longitudinal data set on publicly traded U.S. manufacturing firms from 1980 to 2003 by combining five different data sources. The first source is the updated National Bureau of Economic Research (NBER) files, which contain information on all USPTO utility patents granted from 1976 to 2006 (3,279,509 patents) and their received citations (23,667,977 citations).[13] We use the information on patents and their citations for building the citation-weighted patent stocks variable as a measure of innovation in equation (1). The second data set we employ is the Compustat Legacy North American Annual Industrial data from Standard and Poors, which contain financial information on the U.S. publicly traded firms.[14]

Third data source, a company identifier file, is used to link the updated NBER patent and citation files by firm names to the Compustat firms.[15] This file is needed because Compustat has a unique code for each publicly traded firm. However, firms can apply for patents either

[13]The updated NBER patent and citation files are prepared by Bronwyn H. Hall, and they are available at: http://elsa.berkeley.edu/∼bhhall/. The original files were from 1963 to 1999, and Hall et al. (2001) provide a detailed explanation of them.

[14]The publicly traded firms are those traded on the New York, American, and regional stock exchanges, as well as over-the-counter in NASDAQ.

[15]The company identifier file is available at http://elsa.berkeley.edu/∼bhhall.

under their own name or under their subsidiaries' names, and patent and citation files do not specify a unique code for each patenting firm. The identifier file has the assignee number of each patenting firm in its patent documents, and its equivalent identifier in the Compustat data source. Our fourth data source is the Thompson Financial SDC Platinum merger data set, which tracks completed mergers. The fifth data set is from Bloomberg that provides the time-varying information on business cycles and capacity utilization, all explained in section 2.1.

We merge the patent and citation files of the updated NBER data set to make use of the citation information, such as count of citations made in each patent document. We then drop withdrawn patents and include only the patents of public firms granted from 1976 to 2006 to be able to match the results to the public firms in the Compustat data set.[16] After these changes, the patent file has 1,355,677 observations.

In the Compustat data set, we use data on the manufacturing sector (SIC 2000-3999) from 1976 to 2006, which results in an unbalanced panel of 7,174 firms with 161,633 observations. Table 2 in the appendix shows that an average public manufacturing firm has a large citation-weighted patent stock (2563), which could imply the importance of innovation for these firms.[17] The sample of publicly traded firms may not be fully representative of all firms in the manufacturing sector; however, our choice is restricted by availability of the data.

In the next stage, we merge the patent and citation information with the manufacturing firms of the Compustat employing the identifier file. Then, we drop the missing values of the Tobin's q, which is used as the control variable for behavioural and Q theories of mergers explained in section 2.1. This leaves us with the total number of observations equal to 77,909, which includes 6,679 unique firms for the period 1976-2006. As explained in section 2, the patent and citation counts are truncated. Thus, we correct for these truncations, and the

[16]According to the USPTO's website, withdrawn patents are those that are not issued (http://www.uspto.gov/patents/process/search/withdrawn.jsp).
Note that the citation data are not limited to public firms.

[17]About 83 percent of firms in our sample belongs to innovative industries, such as computers and communications, drugs and medical, electrical and electronics, and mechanical.

correction approaches are explained in appendix A. Similar to Hall et al. (2005), we limit the combined Compustat and patent files to 1976-2003 after corrections to avoid potential problems that might arise from truncations as well as the suggested edge effects by Hall et al. (2005). Therefore, our sample of analysis is limited to when the data are least problematic.

The SDC merger information is from 1980 to the present. Considering our other employed data sources, explained above, we limit the SDC data to the U.S. manufacturing target and acquiring firms from 1980 to 2003. As a result, the SDC provides us with 1,566 unique acquiring companies and 2,075 unique target companies. Then, to add the SDC merger information to the combined Compustat and patent files, we hand-match each SDC acquiring and target firm's name to the Compustat names. This leaves us with 1,064 matches in acquiring companies and 1,528 matches in target companies to the company names in the combined Compustat and patent files. We note that SDC data also provide information on mergers of private acquirers. Nevertheless, the balance sheet information in other standard data sources is not available for such acquirers. Thus, similar to Komlenovic et al. (2011) and Moeller et al. (2004), we do not consider the information of such mergers.

Using our hand-matched names of the SDC acquiring companies to the Compustat firm names, we add the merger data to the combined Compustat and patent files. The number of merging firms in the combined Compustat patent files is not equal to the number of hand-matched names from the SDC to the combined Compustat and patent files. The reason is that the same firm appears in the combined Compustat patent file and the hand-matched names from the SDC but not for the same time period. Additionally, in some of the merging pairs (only about 140 cases), we can not observe the acquiring company in the post-merger period. We can offer two possible explanations. Sometimes firms merge, and the merged entity takes a totally different name. Unfortunately, the SDC merger data source does not offer any information on such name changes. The lack of observation in the post-merger period might also be related to the fact that the merger happened right at year 2003, while the range of the sample under analysis is up to 2003 because of the limitation in other data sources explained above. As a result, we cannot track the merged entity in the post-merger period. We eliminated these mergers from our analysis.[18] As a result, there remain 877 pairs of mergers with 6,741 observations. Note that some of the acquiring firms experience several mergers during the sample period and we keep them all in the sample.

The combined Compustat, patent, and SDC merger data set has observations for both merging and non-merging firms. In cases of mergers, the acquiring firms are observed in the pre-merger periods and the merging year, merged entities are observed in the post-merger period, and target companies are only observed at merging year. To incorporate the pre-merger information of target firms, we employ our hand-matched SDC target names to the Compustat firms and locate each target's pre-merger information among Compustat firms. Then, we hand-match this information to the combined Compustat and patent files for targets in the pre-merger period. This means that, we observe both target and acquiring companies in the pre-merger period and the merging year. In the post-merger period, we observe merged entities. In the next step, we added the information on business cycles and capacity utilization from Bloomberg to the combined Compustat, patent, and SDC merger data set. The resulting baseline sample and data set, used in our estimations, is an unbalanced panel of 6,030 publicly traded merging and non-merging manufacturing firms with 60,736 observations from 1980 to 2003. Of course, the exact number of observations depends on the regression model employed.

Table 2 in the appendix presents the descriptive statistics of all variables, and Table 3 is the correlation matrix of key variables in equation (1). Figure 1 in the appendix shows an overall increasing trend in the number of mergers among publicly traded U.S. manufacturing firms in the sample. The sharp decline in the early 21st century coincides with the 9/11 attack, corporate scandals, and the collapse of internet bubble (Pepall et al., 2011, p.285).[19] Figures 2 also displays the total amount of the citation-weighted patent stock

[18] Furthermore, about 872 cases of mergers are repurchases; we also eliminated these mergers from our study.

[19] The sharp decline of mergers in the latest period of our sample is further associated with eliminating mergers that occurred in the ending year of our sample, 2003; we cannot observe these mergers in the

($CitationPatent$) in each year. Upward trends in Figures 1 and 2 and the correlation matrix in Table 3 point to a positive correlation between mergers and $CitationPatent$. Figure 3 also illustrates the average of the percentage change in the citation-weighted patent stock ($CitationPatent$) of merging and non-merging firms. The firms that experience mergers have generally a higher percentage change in their citation-weighted patent stock in comparison to non-merging firms.

4 Results

We estimate equation (1) presented in section 2 to investigate the impact of innovation on the likelihood of mergers. Our results are reported in Table 4. The first column shows the estimation results, controlling for business cycles (BC_{t-1}) as well as neoclassical theory of mergers. Column (2) adds controls for other theories of merges, i.e., behavioural and Q theories. The third column includes the rest of the controls suggested in the literature and explained in section 2.1. To avoid inconsistent estimates due to unobserved firm heterogeneities, we estimate Columns (1) to (3) of Table 4 using a fixed effect panel logit estimator. The standard errors are all bootstrapped standard errors.

The impact of innovation ($logCitationPatent_{it-1}$) on merger likelihood is positive and statistically significant in all specifications presented in Columns (1) to (3).[20] The estimated coefficient in Column (3) implies that increasing innovation increases odds ratio of merger by 25%. Following Cameron and Trivedi (2010), the calculation of marginal effects of a fixed effect logit estimator for panel data requires estimating firm unobserved heterogeneities which is not feasible. Thus, we interpret results based on the odds ratios. We also report the average probability of the predicted merger conditional on positive outcomes (having a merger experience) for each firm over time. The average predicted probability of merger participation is 0.114 or 11%. The variable $Dnopatent_{it}$ is an indicator variable which

post-merger.

[20]The variable $logCitationPatent$ is in a lagged format to capture the delay in the effect of innovation on merger decisions of firms.

takes a value equal to 1 if the firm is not patenting or has no citation on its patents and zero otherwise. This variable shows a negative effect on merger likelihood in Column (3), which can imply that the probability of mergers is lower for non patenting firms but this effect is not statistically significant. The positive and statistically significant impact of $logCitationPatent_{it-1}$ implies that among firms with patents, the higher citation-weighted patent stock in the previous period increases their current likelihood of mergers. This finding is consistent with Kaplan (2000, p.5), who reports a role for innovation in merger decisions. A further implication of this finding is that innovative firms may utilize mergers to capture their knowledge spillovers and dampen competition (Kats and Shelanski, 2005). Additionally, these firms may use mergers to find external financial sources for commercializing their innovation rather than using their internal sources.

The impact of business cycles (BC_{t-1}) on manufacturing firms' merger decision is positive and statistically significant across all models in Columns (1) to (3).[21] This finding conforms to the idea of procyclicality of mergers suggested by Becketti (1986), Jensen (1993), Maksimovic and Phillips (2001), and Shleifer and Vishny (1992). The expectation of higher demand during booms encourages mergers, as they increase the production capacity to meet the higher demand faster.

Among the six control variables representing industry shocks to capture the industry shocks in the neoclassical theory, only the impacts of asset turnovers ($AssetTurnover_{it}$) and employee growth ($EmployGrowth_{it}$) are statistically significant, and this result persists across Columns (1) to (3). Contrary to the literature that suggests a positive effect of industry shocks on mergers, our results show a negative effect from asset turnovers on the likelihood of mergers. As we add the control variable for behavioural and Q theories of mergers ($Tobin'sq_{it}$) to Column (2), the impacts of industry shocks do not change. The estimated coefficient of $Tobin'sq_{it}$, as a measure of over valuation effect, is positive but not statistically significant. The negative impact of Tobin's q on the probability of merger

[21] The effect of BC_t is also positive and significant, but smaller than BC_{t-1} effect.

conforms to the hypothesis of the excess capacity in Danzon et al. (2007). They argue that firm's with the anticipation of higher growth will have a larger Tobin's q and less incentive to merge, but firms with limited prospects will have less future cash flows and, consequently, smaller Tobin's q. Thus, the merger likelihood could be negatively correlated with Tobin's q. However, we lay limited emphasis on the negative impact of Tobin's q in our findings, as it is not statistically significant. The negative and statistically significant estimated coefficient of HHI_{jt} in Column (3) indicates that higher concentration in the industry of acquiring firms lowers the likelihood of merger. The positive coefficient of $CapacityUtil_t$ also indicates that the annual capacity utilization promotes merger activities.

To address potential caveats in our results, we perform a number of robustness checks with respect to the estimation methods and alternative specifications and measurements. First, although the Hausman specification test supports the fixed effect panel logit estimator, using the fixed effect panel logit estimator decreases the number of observations considerably. The fixed effect panel logit estimator eliminates firms without within group variation in terms of their mergers. In other words, non-merging firms are eliminated. As a robustness check and to avoid selection bias, we also estimate the model in Column (3) of Table 4 with a random effect panel logit estimator and report the result in Column (4) of Table 4. The effect of innovation on merger decision is still positive and slightly higher than that reported in Column (3). The standard errors of column (4) are robust standard errors.

Second, the other concern about our findings might be the possible endogeneity problem in the impact of innovation on merger likelihood raised in the previous studies, such as Schumpeter (1942) and Arrow (1962), and discussed in section 2. We use lagged values of citation-weighted patent stocks of acquiring companies as instruments ($logCitationPatent_{it-2}$ and $logCitationPatent_{it-3}$) to address the endogeneity problem in the model. As the citation-weighted patent stock measure treats the value of each patent equal to its number of citations received, using lagged values of this variable as instruments is relevant because the citations received to patent documents of firms in previous years should not be correlated with their current merger decisions. Table 5 reports the first and second-stage IV regression results. Columns (1) and (2) employ $logCitationPatent_{it-2}$ and $logCitationPatent_{it-3}$ as instrument, respectively. Column(3) uses both of the instruments. These variables are all explained in section 2.

The coefficient estimates of all instruments in Columns (1) to (3) of Table 5 are positive and statistically significant at 1% level of significance. This finding conforms to the idea that innovative firms build a knowledge base that feeds into their future innovative activities. Furthermore, the first-stage F-statistics is large across all columns, rejecting the null hypothesis that the estimated coefficients of the instruments are equal to zero. This reduces concerns that second-stage estimates might be unreliable. The overidentifying restrictions test results for the specification in Column (3) indicates that the hypothesis of exogenous instruments could not be rejected.[22] These results imply that the instruments in Column (3) of Table 5 can explain variations in merging decisions, while uncorrelated with error terms. The results obtained from the second-stage IV estimations are consistent with those reported earlier. Specifically, the instrumented impacts of citation-weighed patent stocks on merger likelihood presented in Table 5 are all positive and statistically significant and not very different in magnitude from corresponding estimates in Table 4.

Third, the citation-weighted patent stock variable might not truly represent innovation, as the connection of innovation to patents is not clear. As a robustness check, we also measure innovation by R&D intensities of firms, which is used by Blonigen and Taylor (2000). As in Hall et al. (2005), we calculate the R&D intensity as a ratio of R&D stock of firms to their book value. R&D stock is built applying the same declining balance formula used for the citation-weighted patent stock measure, and book value (TA_{it}) is explained in section 2.1. Consistent with the previous results, the estimated impact of R&D intensity on merger decision is positive and statistically significant (0.043, Std.Error=0.005) for the man-

[22] We apply the method outlined in Wooldridge (2002). We first estimate equation (1) and obtain predicted residuals. We then calculate NR^2 from a regression of estimated residuals on instruments. Our estimated test statistics is equal to 4.157, and we can not reject the hypothesis of exogeneity of instruments.

ufacturing sector.[23] Forth, target companies' innovation might also play a role in acquiring companies' decisions to merge (Danzon et al. 2007). At times, when the acquiring firm does not have a good research prospect, it might go after firms with more effective innovation. To address this concern, we also control for the the logarithm of citation-weighted patent stocks of target companies at merging year in a model based on Column (3) of Table 4. The effect of this variable is not statistically significant and the positive effect of innovation on merger likelihood (0.292, Std.Error=0.072) is robust to the inclusion of this variable. We also estimate the model of Column (3) of Table 4 using the suggested first principal component variable of Harford (2005), explained in section 2.1, to control for industry shocks of the neoclassical theory of mergers. The estimated coefficient of the variable of interest $logCitationPatent_{it}$ stays positive and statistically significant (0.334, Std.Error=0.049).

4.1 Innovation Impact by Industry

The firm's decision on merger may well be industry-specific and, therefore, we need to control for the industry as well as the firm characteristics. Similar to Hall et al. (2005), we construct six industry categories as follows: $Chemicals$, $Computers$, $Drugs$, $Electricals$, $Mechanicals$, and $OtherIndustries$.[24] The number of firms and the number of mergers in each industry in the sample are: $Chemicals$: 174, 21; $Computers$: 337, 28; $Drugs$: 1089, 87; $Electricals$: 1250, 99; and $Mechanicals$: 866, 91.

To capture the impact of innovation on merger likelihood at the firm level in each industry, we include interaction terms of the first lag of the citation-weighted patent stocks with an indicator variable for each industry in equation (1). The coefficients of the interactive terms

[23] This is contrary to the finding of Blonigen and Taylor (2000) that relatively low R&D firms have a larger likelihood of participation in acquisition market in the U.S. electronics and electrical equipment sector. Blonigen and Taylor (2000) measure merger with the number of annual mergers and use a sample of the U.S. electronics and electrical equipment firms from 1985 to 1993.

[24] *Chemicals* includes chemical products, *Computers* consists of the computers and computing equipment, and *Drugs* includes optical and medical instruments, and pharmaceuticals. *Electricals* contains electrical machinery and electrical instrument and communication equipment, and *Mechanicals* includes primary metal products, fabricated metal products, machinery and engines, transportation equipment, motor vehicles, and auto parts.

show the marginal impact of innovation on merger in an industry compared to that in the reference group ($OtherIndustries$). Table 6 reports the results, according to which the total impact of innovation on merger likelihood in each industry is $Chemicals$, 0.257 (Std.error=0.155), $Computers$, 0.255 (Std.error=0.095), $Drugs$, 0.355 (Std.error=0.063), $Electricals$, 0.311 (Std.error=0.055), and $Mechanicals$, 0.286 (Std.error=0.055). The total impacts are all positive and statistically significant, which imply a heterogeneous impact of innovation on merger likelihood across industries.

To further analyze industry effects, we also adopt a multilevel approach and focus on the more detailed industry classifications SIC4. The multilevel approach suggests that ignoring information about a level (industry) that is correlated with the original level of interest (firms) can lead to biased estimates of the firm level coefficients (Moshiri and Simpson, 2011). We employ a mixed model estimation method where we use firms as the first level and four-digit SIC codes to define industries of firms as the second level. The estimation model is

$$y_{ij} \quad = \quad c_j + \gamma_j X_{ij} + \alpha_i + \epsilon_{ij}, \tag{2}$$

where the levels are i, for firm, and j, for industry. The vector X_{ij} includes all explanatory variables in equation (1), and α_i controls for firm unobserved heterogeneities. ε_{ij} is an idiosyncratic error term with the standard features: $E(\varepsilon_{ij})$=0, $Var(\varepsilon_{ij})$=σ^2_ε. We assume that both the intercept and slope vary according to level j. For example, if y_{ij} and X_{ij} represent firm i's merger decision and innovation in industry j, then the merger-innovation relation is subject to unobserved industry effects and is, therefore, expected to vary across industries. In most applications, it is customary to assume that the unobserved j-level effects are not correlated with covariates. The model can therefore be specified as follows.

$$
\begin{aligned}
c_j &= c + u_j \\
\gamma_j &= \gamma + v_j \\
E(u_j) &= E(v_j) = 0 \\
Var(u_j) &= \sigma_u^2, Var(v_j) = \sigma_v^2, Cov(u_j, v_j) = \sigma_{uv} \\
E(u_j x_{ij}) &= E(v_j x_{ij}) = 0
\end{aligned}
$$

In a special case, also called the variance component or random intercept model, where only the intercept varies across level j, that is v_j=0, the variance-covariance matrix of the model is

$$
\Omega_m = \begin{pmatrix} \sigma_u^2 J + \sigma_\varepsilon^2 I & . & 0 \\ . & . & . \\ 0 & . & \sigma_u^2 J + \sigma_\varepsilon^2 I \end{pmatrix}
$$

where m is the dimension of the matrix, and I and J are an (n x n) identity matrix and a matrix of ones, respectively. If it is assumed that the unobserved j-level effects are uncorrelated with the covariates (x), it would mean that the level effect in the hierarchical structure of the data is random. In this model, therefore, firm behaviour can be explained both by observed firm characteristics and observed and unobserved higher level factors. In other words, the mix or multilevel model implies that firms whose behaviours are highly correlated are grouped in clusters (higher levels), and the firm outcomes can be explained by observed and unobserved factors within a cluster (intracluster heterogeneity) as well as by observed and unobserved differences between clusters (intercluster heterogeneity). The multilevel or mixed model above can be estimated by using the Iterated General Least Squares or Restricted Maximum Likelihood Estimation method, both of which produce unbiased estimates

(Wooldridge, 2002; Goldstein, 2003). In this study, we use a mixed model to estimate the impact of innovation on the merger likelihood of firms, thereby controlling for a series of observed and unobserved factors at the firm and industry levels.

Table 7 reports the results based on the mixed model estimation method. Columns (1) to (3) show that the impact of citation-weighted patent stocks on merger decision is positive and significant, and its magnitude is comparable to those obtained earlier. The intra industry correlation is statistically significant across all columns. This correlation shows the degree of dependence between observed responses on two firms from the same industry. Additionally, the likelihood ratio test clearly rejects the ordinary logistic model in favour of the mixed model. Therefore, our results on the innovation impact of mergers are robust to the mixed model estimation methods. The new results also reconfirm the heterogeneous innovation impacts on merger likelihood across industries.

5 Conclusion

Innovative firms use mergers to provide resources for commercialization of their innovation and capturing their knowledge spillovers. Despite the convincing arguments offered in the literature on the impact of innovation on mergers, there is only limited empirical evidence on the effect and its consequences for market structure. The previous studies on merger activities have used different factors affecting mergers mostly at the industry level, which masks the disaggregated information on firm level decision-making process. We contribute to the merger literature by focusing on the innovation factor in merger decisions at the firm level.

Our analysis is conducted using unbalanced panel data on more than 6,000 publicly traded merging and non-merging U.S. firms in the manufacturing sector from 1980 to 2003. A unique aspect of our data set is that, contrary to previous studies, it includes information on target companies in the pre-merger period for each of the merging pairs of firms as well as non-merging firms in the data.

Our results show that innovation measured by the citation-weighted patent stocks increase the merger likelihood of firms. The instrumented impacts of innovation on the probability of merging also show positive and comparable effects from innovation. This result implies that the internalization of knowledge spillovers and the need for resources to commercialize innovation create incentives for firms to merge. Our findings also support the procyclicality of mergers at the firm level. Moreover, our result on Tobin's q supports the hypothesis of the excess capacity of Danzon et al. (2007), but the role of the relative valuation of firms in merger decisions based on behavioural and Q theories are not significant. Finally, the impact of innovation on merger decisions is conditional on acquiring companies' industries, which might imply a need for treating merger applications of various industries differently.

Our findings offers some insights for anti-trust policies, as they provide evidence for the positive role of innovation in merger activities and market structure for the manufacturing sector. Thus, the anti-trust authorities should weigh the loses associated with decreasing competition against the benefits of promoting innovation through mergers, when deciding on merger applications.

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Figures and Tables

Figure 1: Number of Mergers by Year in Sample.

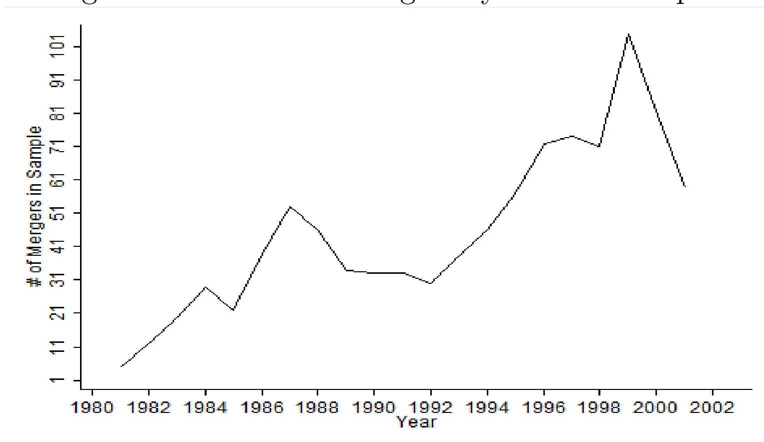

Figure 2: *CitationPatent* by Year in Sample.

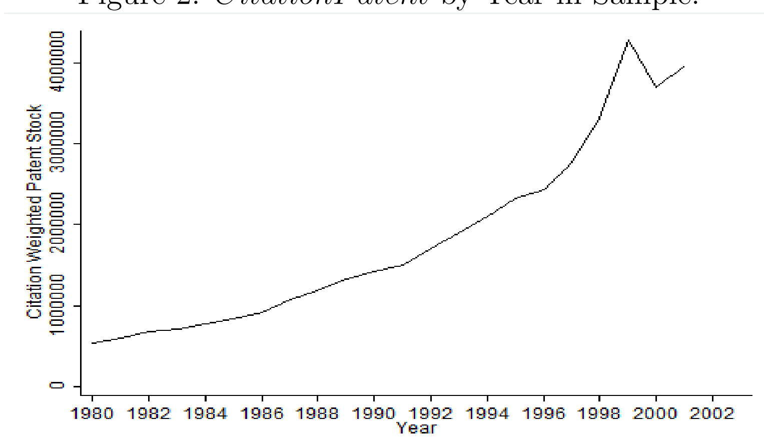

Figure 3: Average of %$\triangle$ $CitationPatent$ of Merging and Non-Merging Firms.

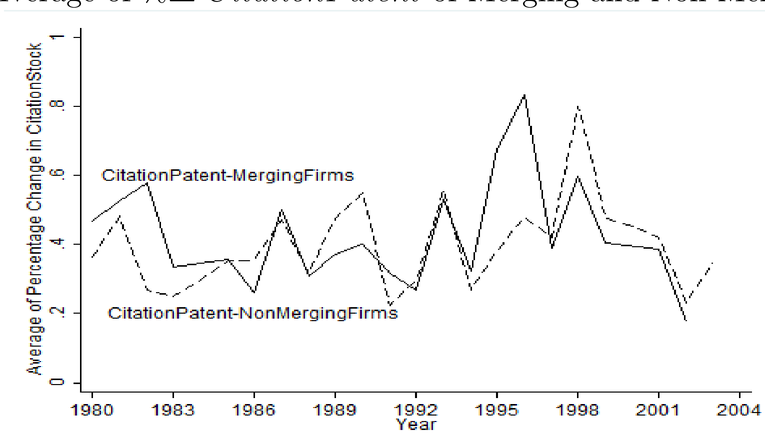

Table 1: Definition of Control Variables

Variable	Definition	Source
BC_t	Chicago Fed National Activity Index (CFNAI)	Bloomberg
$AssetTurnover_{it}$	The ratio of sales to total asset	Compustat and authors' calculations
$EmployGrowth_{it}$	The growth of the number of employees	Compustat and authors' calculations
$SaleGrowth_{it}$	The growth of firm level sales	Compustat and authors' calculations
$Profitability_{it}$	The ratio of net income to sales	Compustat and authors' calculations
ROA_{it}	Return on assets	Compustat
$CapitalExp_{it}$	Expenditure on property, plant, and equipment	Compustat
HHI_{jt}	Concentration in the industry of each firm calculated from the summation of squared market shares. Market share is the ratio of each firm's sales to total sales of primary four-digit SIC4 that the firm belongs to.	Compustat and authors' calculation
$Tobin'sq_{it}$	The ratio of market value to book value	Compustat and authors' calculations
$Cash_{it}$	Cash and cash equivalent	Compustat
$ExcCash_{it}$	Cash and cash equivalent in current year minus arithmetic mean of cash over the sample period	Compustat and authors' calculations
$(Debt/Equity)_{it}$	(total debt/shareholder equity)$\times$100	Compustat and authors' calculations
$CapacityUtil_t$	Maximum output utilized in an industry	Bloomberg

Table 2: Descriptive Statistics

Variable	Obs	Mean	Median	Std.error	Min	Max
$Merger_{it}$	6736	0.017	0	0.128	0.000	1.000
$logCitationPatent_{it}$	18646	5.70	5.57	2.017	-2.146	12.057
BC_t	60736	0.051	0.099	0.823	-2.434	1.441
$AssetTurnover_{it}$	60570	1.171	1.111	0.820	-0.149	54.962
$EmployGrowth_{it}$	51740	0.184	0.018	4.799	-1	691
$SaleGrowth_{it}$	55343	0.954	0.086	48.854	-56.294	7731
$Profitability_{it}$	59288	-3.120	0.030	73.425	-8684	1332
ROA_{it}	60553	-0.168	0.035	4.497	-861.31	305
$CapitalExp_{it}$	59863	99.771	3.476	643.74	-1.604	33143
HHI_{jt}	60736	0.285	0.240	0.188	0.000	1
$Tobin'sq_{it}$	60736	4.024	0.795	79.948	0.000	10322
$logCash_{it}$	53029	0.581	0.000	1.917	-6.908	9.164
$logExcCash_{it}$	53024	0.430	0.000	1.969	-23.677	9.030
$(Debt/Equity)_{it}$	59768	175500	1999	3855745	-230	0.000
$CapacityUtil_t$	60736	80.451	81.07	3.387	71.401	84.90

Notes: Our sample period is an unbalanced panel of 6,030 merging and non-merging manufacturing firms with 60,736 observations from 1980 to 2003.

Table 3: Correlation Matrix

	$Merger_{it}$	$CitationPatent_{it}$	BC_t	$AssetTurnover_{it}$	$Tobin'sQ_{it}$
$Merger_{it}$	1.000				
$CitationPatent_{it}$	0.208	1.000			
BC_t	0.033	0.009	1.000		
$AssetTurnover_{it}$	-0.050	-0.049	-0.023	1.000	
$Tobin'sQ_{it}$	-0.005	-0.007	-0.010	-0.042	1.000

Table 4: The Estimation Results for Merger Decision

Dependent Variable $Merger_{it}$	(1)	(2)	(3)	(4)(RE Model)
$logCitePatent_{it-1}$	0.181***	0.293***	0.254***	0.274***
	(0.031)	(0.061)	(0.061)	(0.031)
BC_{t-1}	0.314 ***	0.348 ***	0.248**	0.252**
	(0.051)	(0.057)	(0.088)	(0.087)
$AssetTurnover_{it}$	-1.232***	-1.178 ***	-1.136***	-0.430***
	(0.177)	(0.256)	(0.270)	(0.130)
$EmployGrowth_{it}$	0.019	0.795***	0.795 ***	0.060 ***
	(0.315)	(0.166)	(0.191)	(0.017)
$SaleGrowth_{it}$	0.069	0.428	-0.067	-0.036
	(0.115)	(0.626)	(0.088)	(0.044)
$Profitability_{it}$	-0.014	-0.035	-0.025	0.002
	(0.033)	(0.144)	(0.069)	(0.002)
ROA_{it}	0.482	-0.000	-0.357	0.118
	(0.318)	(0.793)	(0.743)	(0.172)
$CapitalExp_{it}$	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
HHI_{jt}			-1.873*	-0.410
			(1.038)	(0.361)
$Tobin'sQ_{it}$		-0.079	-0.109	-0.192**
		(0.162)	(0.179)	(0.071)
$logCash_{it}$			0.003	0.227***
			(0.073)	(0.048)
$logExcCash_{it}$			0.053	-0.047
			(0.061)	(0.037)
$(Debt/Equity)_{it}$			0.000	-0.000
			(0.000)	(0.000)
$CapacityUtil_t$			0.042*	0.054**
			(0.024)	(0.020)
$Dnopatent_{it}$	0.037	0.039	-0.067	0.049
	(0.169)	(0.277)	(0.224)	(0.199)
Observation	7758	3083	2707	23257
Firm FE	Yes	Yes	Yes	No

Notes: The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are bootstrapped standard errors.

Table 5: Instrumental Variable Estimates of Mergers and Innovation

First-Stage IV			
Panel Fixed Effects Estimator			
Dependent Variable	(1)	(2)	(3)
$logCitePatent_{it-1}$			
F	84.19	207.71	194.84
P-value	[0.000]	[0.000]	[0.000]
$logCitePatent_{it-2}$	0.395***		0.303***
	(0.014)		(0.014)
$logCitePatent_{it-3}$		0.307***	0.188***
		(0.016)	(0.014)
Second-Stage IV			
Panel Logit Estimator			
Dependent Variable			
$Merger_{it}$			
$logCitePatent_{it-1}$	0.192***	0.230***	0.174***
	(0.056)	(0.052)	(0.052)
Control Variables in Equation (2)	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observation	2651	2585	2585
Overidentifying Restrictions J-test and χ^2			4.157 [5.024]

Notes: The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are the clustered standard errors in the first stage and bootstrapped standard errors in the second stage.

Table 6: The Industry Effects of Merger Decision

Dependent Variable: $Merger_{it}$	$logCitePatent_{it-1}$ $\times Chemical$	$logCitePatent_{it-1}$ $\times Computer$	$logCitePatent_{it-1}$ $\times Drugs$	$logCitePatent_{it-1}$ $\times Electrical$	$logCitePatent_{it-1}$ $\times Mechanical$
Marginal	0.018	0.016	0.116	0.072	0.046
	(0.161)	(0.110)	(0.087)	(0.089)	(0.081)
Total	0.257*	0.255**	0.355***	0.311***	0.286***
	(0.155)	(0.095)	(0.063)	(0.055)	(0.055)

Notes: The signs ***, **, and * mean significance at 1%, 5%, and 10%,respectively. The numbers in the parentheses are the bootstrapped standard errors. Estimates are based on equation (1) and estimated with a panel logit estimator. Number of observations is 16,476.

Table 7: The Mixed Model Estimation Results On Merger Decision

Dependent Variable $Merger_{it}$	(1)	(2)	(3)
$logCitePatent_{it-1}$	0.318***	0.316***	0.263***
	(0.016)	(0.016)	(0.024)
BC_{t-1}	0.330 ***	0.342 ***	0.250**
	(0.044)	(0.045)	(0.079)
$AssetTurnover_{it}$		-0.311 ***	-0.234**
		(0.069)	(0.104)
HHI_{jt}			-0.756**
			(0.358)
$Tobin'sQ_{it}$			-0.038 *
			(0.023)
$logCash_{it}$			0.279***
			(0.038)
$logExcCash_{it}$			-0.089***
			(0.028)
$(Debt/Equity)_{it}$			-0.000
			(0.000)
$CapacityUtil_{t}$			0.048**
			(0.018)
$Dnopatent_{it}$	0.130	0.141	0.094
	(0.114)	(0.114)	(0.168)
Number of Firm Level	54705	54625	26580
Number of Industry Level	219	219	219
Intra Industry Correlation	0.68	0.72	0.67
	(0.071)	(0.073)	(0.089)
LR Test Versus	143.98	146.98	51.38
Logistic Regression	P(0.000)	P(0.000)	P(0.000)

Notes: The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively.
levels are firms and industries, respectively.
The numbers in the parentheses are standard errors.

Appendices

A Correcting Truncation in Patent and Citation Counts

To address the plausible truncation in patent counts, we adopt the approach of Hall et al. (2000), which defines weight factors to correct for truncation in patent counts. The weight factors for our study are calculated according to

$$\begin{aligned} PatentCount_t^* &= \frac{PatentCount_t}{\sum_{J=0}^{2003-t} Weight_J} \\ 2000 &\leq t \leq 2003, \end{aligned} \tag{A.1}$$

where $PatentCount_t$ is the number of patents granted at time t to all firms and $Weight_J$ is built based on the average of citations in each lag for the patents of firms. Lags are defined as the difference between the ending years of the sample and the last year of the sample, year 2003. Therefore, lags are 2003-2000=3, 2003-2001=2, 2003-2002=1, and 2003-2003=0. Hall et al. (2000) multiply the count of patents in ending years of the sample (2000-2003) with the inverse of the weight factors ($1/PatentCount_t^*$) and correct for the truncation. We only correct patent counts for 2000 to 2003 because following the argument of Hall et al. (2000), from 2004 to 2006, when the patent and citation files in this research end, the results are under the influence of "edge effect". Hall et al. (2000) explain that the "edge effect" makes the very last years of patenting and citation data unusable, and they have very large variances. Figure A.1 displays a comparison of original patent counts to the corrected patent counts for truncation.

To address the truncation in citation counts, we also follow the method of Hall et al. (2000). We calculate the distribution of the citations received by each citing patent between the grant year of the citing patent and the grant year of the cited patent in the patent document of the citing patent. Then, using this distribution, we forecast the number of citations that might be received for each citing patent outside the range of the sample up to 40 years after the grant date of the citing patent. Figure A.2 illustrates a comparison of original citation counts to corrected citation counts. The truncation corrected patent and citation counts are used in this paper.

Figure A.1: Patents per $R\&D$ with Corrected and Uncorrected Patent Counts.

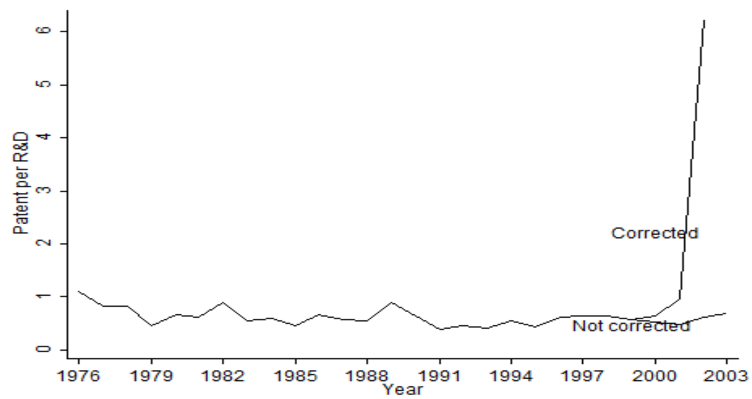

Figure A.2: Citations per $R\&D$ with Corrected and Uncorrected Citation Counts.